CHAPTER SIX

Energy Harvesting for Sustainable Smart Spaces

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Abstract

Energy sustainability is a challenge in making smart spaces truly pervasive. Renewable energy technologies have become a promising solution to reduce energy concerns

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that arise due to limited battery in wireless sensor networks, the backbone of many smart spaces. While this enables us to prolong the lifetime of a wireless sensor network (perpetually), the realization of such sustainable micro-scale energy harvesting system is challenging due to the unstable nature of environmental energy sources and demanding requirements of applications. In this chapter, we show the model of micro-scale energy harvesting system and research efforts both in designing low-power efficient hardware platforms and in creating software components to operate micro-scale energy harvesting systems at their maximum potentials. We highlight the need of deployment study of micro-scale energy harvesting systems in addition to designing and operating research and propose middleware architecture for a unified structured way to optimize energy harvesting system performance.

1. INTRODUCTION

Advances in technology have made pervasive computing vision feasible, a vision that the world we live would be surrounded by networked specialized hardware and software, all weave themselves into everyday activities or deeply integrated into everyday objects [1]. Twenty years after this groundbreaking vision, pervasive computing research is believed to have gone through three generations of research from *connectedness* to *awareness* then to *smartness*[2].

Since late 1990s, when networks of pervasive systems emerged, computing systems started connecting together using both wire and wireless protocols, allowing applications to spread and provide services to multiple systems simultaneously. Furthermore, it enables collecting and sharing information at a much larger scale. The initial vision of Weiser has become practical through handheld devices, tabs, Internet, and wireless sensor networks (WSNs), just to name a few. Based on this foundation, a new concept called "context-awareness" later emerged; in which pervasive systems do not only provide static computing and information services but they are also equipped with sensor networks and processing technologies to capture data and construct knowledge of environment and system states. Given this awareness of situations and their resources, pervasive systems are able to adapt themselves autonomously and accordingly to their contexts. Grounded on the foundation of connectedness and awareness, pervasive computing systems take a step further and use more advanced sensor technologies to capture and understand user needs and concerns in order to configure and to transform themselves accordingly. This transformation coined the term "smartness." Ongoing research in pervasive computing has even more ambitious goals, they envisage pervasive computing systems with advanced capabilities such as continuous lifelong learning, true understanding of users' mental and emotional situations, and adapting to user needs to maximize their satisfaction [2].

Smart spaces are potential platforms where pervasive computing can be realized. In fact, one of the first research thrust was on effective use of smart spaces [3]. Smart spaces mostly refer to enclosed well-structured areas such as a building, a house, a meeting room whose physical infrastructure is well integrated with computing, communication technologies, and energy systems. Smart spaces are extended to larger scale (and/or open) spaces and more sophisticated areas such as an instrumented campus composed of several smart buildings, smart parking lots, and smart outdoor spaces (e.g., Responsphere infrastructure on UCI campus [4]). In the subsection below, we briefly give an overview of several smart spaces examples.

1.1 Examples of Smart Spaces

Smart space applications can be categorized into two types: (a) periodic monitoring and service providing applications and (b) emergency-response applications. In a periodic monitoring and service providing application, smart spaces goal is to provide continuous services and assistance to users, to make their lives easier and more effective. Examples of smart spaces are smart homes [5–7].

Helal et al. [5] propose an ambitious and intelligent platform for a smart home that encapsulates smart technologies in various locations. These include smart plugs, smart projectors, smart displays, and smart floors (see Fig. 1). The goal of the project is to provide continuous services and assistance to senior people and people with disability.

Behind the physical devices and appliances in such a smart home is a sensor/actuator network to support the platform that "effectively converts any sensor or actuator in the physical layer to a software service that can be programmed or composed into other services." In this assistant environment, physical items inside the residential area are virtually connected together. They are monitored to gain holistic knowledge of the smart space systems, environment, and people occupancy; hence providing awareness to the upper layers. Applications then control the physical environments through actuators and provide information as well as comprehensive services to the users. Interestingly, a group of sensors, actuators, and services could be combined together at the software layer to create more sophisticated sensing and actuating applications. This platform is robust and open to changes at both the physical layer, in which new sensors can be added, and at the application layer, in which new services could be integrated. The mechanism of the middleware layer is programmable.

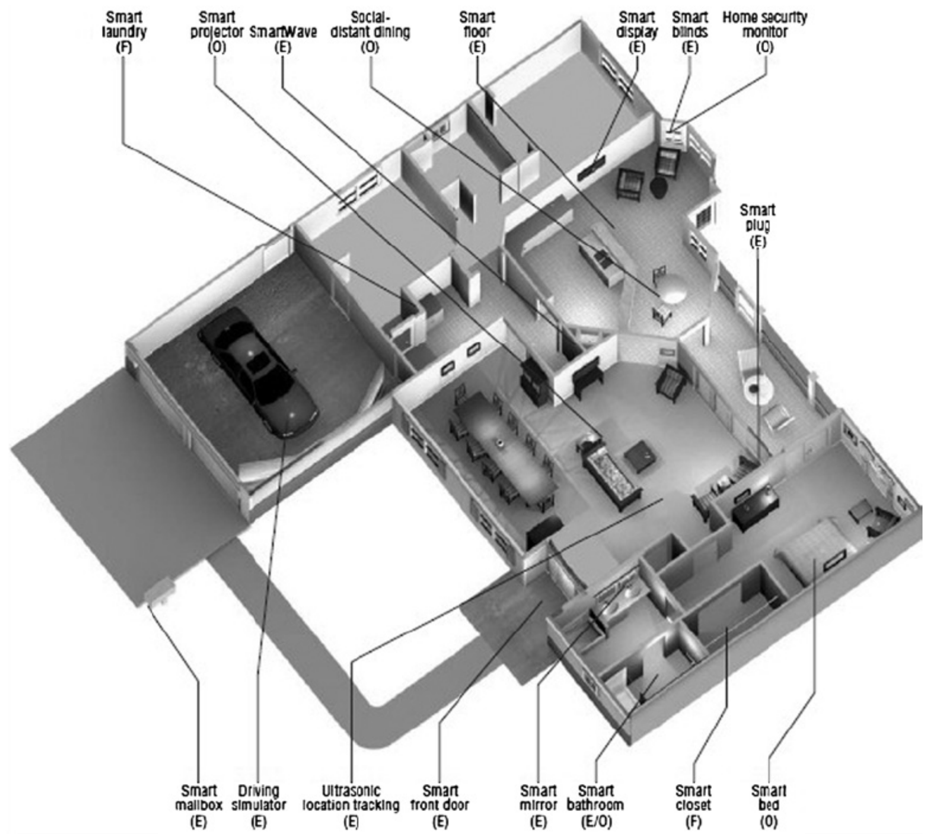

Fig.1. The gator tech smart house [5].

Emergency-response applications may also consist of periodic monitoring components but their main goal is not to provide daily services to the users but to keep track of changes in the environment or infrastructure of smart spaces. The systems are designed to quickly detect failures and critical events, to notify people in charge and assist them in avoiding or managing catastrophe. Examples of failures in a smart space are damaged structures of bridges, large traffic systems, ships or avionic systems. Critical events can be earthquake, flood, or fire.

Responding to Crisis and Unexpected Events (RESCUE) project [8] is another example of instrumented smart spaces but for emergency response. Their main goal is "dramatically improving the ability of emergency response organizations… during man-made and natural catastrophes." This project consists of several sub-projects: situational awareness, information sharing, robust communications, information dissemination, and privacy protection. Figure 2 shows the RESCUE's infrastructure for emergency response systems [88]. Each of the sub-systems focuses in one important aspect, from gathering and processing static and mobile data (robust communications),

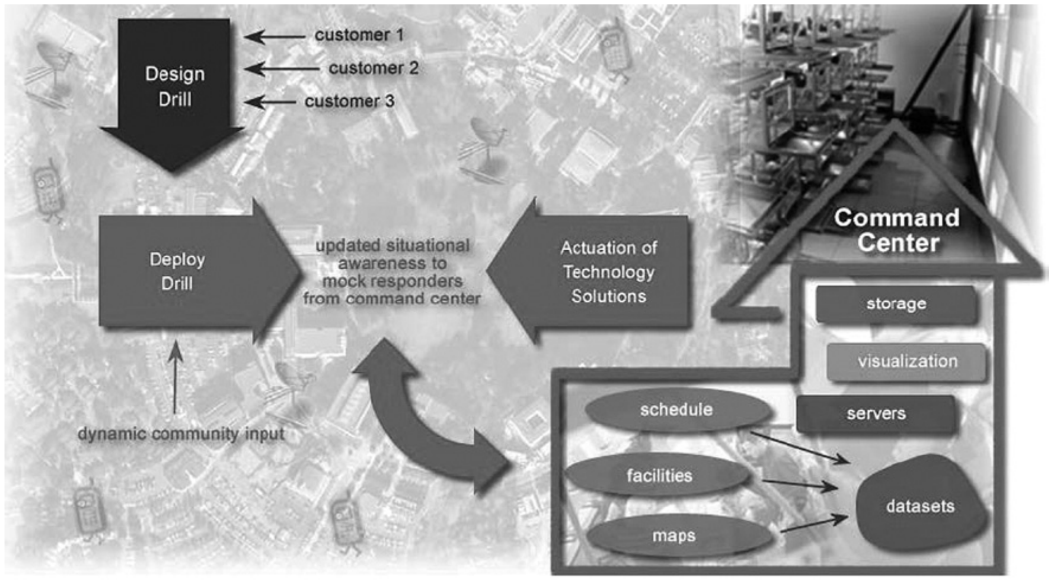

Fig. 2. Responsphere infrastructure.

managing and using data (situational awareness, information sharing) to disseminate information (information dissemination, privacy). Altogether, they make the vision of the final RESCUE system practical and feasible. This is an example demonstrating that technologies can enable smart spaces at a larger scale incorporating mobile and emergency factors.

Other applications of smart spaces involving heavy use of wireless sensor networks include health applications (drug administration, human physiological data monitoring), structural health monitoring, environmental monitoring (volcano, forest fire, and flood detection), and battlefield surveillance [37].

- *Body sensor network—wearable devices* (e.g., [9]): A network of wearable sensors is attached to human body to monitor and collect data about user health and state. This information is sent via wireless to a local base station also attached to the human where data is processed, stored, or sent to a remote station such as a clinic or doctors' server. Beside performance requirements, safety and reliability are important challenges in these critical applications. The system must be available, meet timing and quality requirements under dynamic constraints such as mobility.
- *Infrastructure and environmental monitoring* (e.g., [90]): In these applications, sensors are deployed in smart spaces to monitor the structures themselves (structural health monitoring) or other properties of the environment (temperature, gas level, etc.). Degree of safety requirement varies from

application to application and the locations where the sensor networks are deployed (e.g., nuclear plan monitoring vs. office building monitoring).

- *Battlefields monitoring* (e.g., [91]): Wireless sensor networks are deployed in battle fields to detect enemy activities. Their requirements include capturing useful information with certain degree of accuracy, utmost security, and stealthiness, having sufficient lifetime and availability. In such a harsh environment, the system must be robust and durable.

Regardless of application types in smart spaces, they share common challenges due to the complexity and heterogeneity of systems, smart interaction requirements with the environment and users as well as needs of adaptation to changes. Next, we present an overview of critical challenges in designing an effective smart space.

1.2 Challenges in Designing Smart Spaces

The dynamicity and complexity of smart spaces pose several challenges which must be taken into account when designing an efficient smart space. We summarize the challenges as follows:

- *Smart and efficiency:* As the name says it all, a smart space must be smart and efficient. It must understand user needs and preferences to provide the best services in an efficient manner, i.e., short response time with high energy efficiency.
- *Scalability:* The scale of smart spaces goes from an enclosed meeting room, a house, a floor to a building, a city, or large bounded/unbounded area such as a campus. Amount of data to be collected and processed and the complexity of control programs grow exponentially according to the scale of smart spaces.
- *Robustness:* Smart spaces keep evolving, changing, and transforming themselves according to their context awareness. At the same time, hardware and software can fail or age and hence must be upgraded or replaced. How a smart space system maintains connection, control, and services despite continuous changing is the robustness challenge.
- *Heterogeneity:* Smart spaces are heterogeneous systems at all level of abstractions. Infrastructure layer must manage variety of devices each with its own operating requirements and characteristics. Information and computing layer has various data streams and protocols for concurrent applications and services. It is a challenge for smart spaces to make all heterogeneous hardware and software components work in concert.

- *Security and privacy:* Since smart spaces need to collect information about user behavior and occupancy in space, security and privacy has become a sensitive problem. For example, a smart meter records electrical consumption of a household. If someone hacks the system to gain access to this data, information about occupant habits and presence can be extracted and exposed to unauthorized people.
- *Resilience:* In a complex system such as smart spaces, failures can occur and services can be terminated. Redundancy and other fault-tolerant mechanisms must be deployed at different layers to provide system resilience.
- *Sustainability:* Sustainability is a key challenge for any system or infrastructure. *By sustainability in a system context, we mean a system is endurable, either well supported or self-sustainable. To achieve this, the system can rely on application adaptation, infrastructure resilience, energy sustainability or all of them.*

In this chapter, we focus in energy sustainability. Energy sustainable systems must have a reliable, dependable power source subsystem or a good power management framework. The systems are durable, have little energy concern, and require minimal maintenance effort.

In all examples of smart spaces in Section 1.1, central platforms always rely on large scale wireless sensor networks (WSNs) instrumented in the physical environment. Wireless sensor networks are sensors with limited memory and processing capability connected together using wireless technologies and protocols. They are the backbone of smart space systems, the eyes and the connection between the computing world and the physical world, making the systems aware and adaptive to changes in the surroundings and system states.

The challenges mentioned above for smart spaces are also applicable to their backboned WSNs, from heterogeneity, scalability to energy sustainability. WSNs deployed in smart spaces must deal with a variety of sensors and data types such as temperature, gas level, motion detection, or image capturing. As more smart applications, services, and devices are integrated into the physical world, WSNs will keep growing from tens to hundreds of nodes in a single smart space. Energy sustainability for a large number of distributed nodes in WSN becomes a crucial challenge. At the same time, they must be able to operate in a non-intrusive way to human life, without intervention and even awareness of the occupants in smart spaces. If energy is distributed to each sensor through wires, plugs, and cables, it is not only intrusive but the deployment process also requires a significant amount of work in set-up, layout, and wiring.

Traditionally, to meet energy sustainability while being non-intrusive, WSNs rely on non-rechargeable limited-capacity batteries. However battery-operated approach presents another challenge. If a sensor mote runs at full duty cycle, it lasts only several weeks. Therefore many sensor motes are set to operate at very low duty cycle, from 1% to 5% to prolong the system lifetime while maintaining minimum acceptable quality of services. Still the batteries last from 6 months to 1 year. As soon as a sensor runs out of battery, occupants or technician must replace exhausted batteries immediately to avoid temporary shutdown in their services or lose access to part of the network or a physical area. In scenarios where changing battery is impossible or too costly due to inaccessibility or high risk such as in volcanoes or battlefields, old sensors must be discarded and new sensors are deployed. Despite many efforts to prolong system lifetime and maintain system performance under power-efficient or energy-efficient requirements, the repetitive high maintenance cost still remains a burden in WSNs. This approach of battery-operated platform will not scale as WSNs for smart spaces grow. Meeting the energy sustainability requirement for backbone WSNs is one of the key challenges in developing efficient infrastructure for smart spaces.

With the emergence of energy harvesting technologies, systems are able to convert energy sources in the surrounding environments into electricity to power them. The systems become energy-independent and last for virtually unlimited time only subject to hardware aging. This emerging technology makes it feasible to build efficient and autonomous smart spaces in which the wireless sensor network is truly energy-sustainable and non-intrusive. Each sensor mote could be equipped to harvest energy from the ambient environment. We define the concept of micro-scale energy harvesting systems as opposed to macro-scale energy harvesting systems (such as solar or wind farms) as follow:

"*Micro-scale Energy Harvesting Systems are small low power devices which have energy harvesting subsystems capable of harvesting energy from the surrounding environment to fully or partially power the whole system, hence attain almost perpetual system lifetime*" (see Fig. 3 for an example).

Energy sustainability and micro-scale energy harvesting systems are the focus of this chapter. We propose energy harvesting as a promising solution to energy sustainability of WSNs in smart spaces. This chapter is organized as follow: In Section 2, we discuss several general energy sustainability approaches in smart spaces and highlight energy harvesting as a suitable solution to energy sustainability of backbone WSNs in smart spaces but with its own challenges. In Section 3, we describe a model for micro-scale

Fig. 3. Example of micro-scale energy harvesting system, QuARES test bed [87].

energy harvesting systems, their components and state-of-the-art techniques to build an efficient system from both hardware and software perspectives. In Section 4, we summarize research challenges in system design, deployment, and operation of micro-scale energy harvesting systems. We summarize and conclude the chapter in Section 5.

2. ENERGY SUSTAINABILITY IN SMART SPACES

Energy sustainability is a key challenge for any system or infrastructure. An energy sustainable system maintains its operation relying on its energy sources, the system do not shut down at critical time because of lack of energy and require little or no manual intervention during its operation.

We present several approaches to energy sustainability in smart spaces below and argue that energy harvesting is the most suitable technique to achieve energy sustainability for WSNs in smart spaces.

2.1 Energy Sustainability Approaches

We show several views and perspectives of energy sustainability in smart spaces beyond WSNs. Approaches for energy sustainability in smart spaces should consider the entire energy system in a holistic way, not only reducing total energy usage and peak load, enabling Smart Grid architecture integration, achieving system sustainability but also considering any side-effects on occupant behaviors, and possible pollutants. To achieve energy sustainability in smart spaces, there have been works proposed in the following categories:

Energy awareness increase: It is important to make building occupants aware of their energy usage by leveraging sensing systems together with novel visualization and other forms of media to convey relevant information to users. This can make an impact or influence their behavior towards a more parsimonious usage of utilities including electricity, gas, heating, water, etc.

Smart buildings, smart apps: Novel approaches are needed to predict, monitor, and actuate the systems in smart spaces in order to reduce energy consumption. The Systems Networking and Energy Efficiency (SYNERGY) Labs at UC San Diego perform multiple research projects in smart buildings [16,17]. The team invented a solution for reducing HVAC energy waste on an experimental floor. The idea was intuitive: employ occupancy sensors that can tell when a room is empty, and have these detectors communicate with a smart controller to adjust the existing HVAC system in real time [18]. Their wireless occupancy sensors are claimed to be easy-to-use and do not require any alteration to existing energy systems. These sensors achieve accuracy of 96% and are calibrated to never assume a room is empty when someone is around.

Smart meters: A smart meter is an electrical meter that records consumption of electric energy in houses in intervals of an hour or less and communicates that information at least daily back to a utility plant for monitoring and billing purposes [19]. Such an advanced metering infrastructure (AMI) differs from a traditional automatic meter reading (AMR) in that it enables two-way communications between a meter and a central system. There is a need for novel infrastructure and communication standards for collecting data from smart meters and energy-related information in smart spaces. However, there are also security and privacy issues related to using smart meters which need to be addressed [20].

Smart materials: Smart materials are those that can adapt themselves to the environment condition and user needs. Smart material such as smart glass (also called smart windows or switchable windows for homes, skylights, and transportation vehicles) refers to electrically switchable glass which changes light transmission properties when a voltage is applied to it [21,22]. Current smart glass technologies include electrochromic devices, suspended particle devices and liquid crystal display. When activated, the glass changes from transparent to translucent, partially blocking light while maintaining a clear view through the glass. In addition, the use of smart glass can save costs for heating, air conditioning, and lighting and avoid the cost of installing and maintaining motorized light screens, blinds, or curtains. Smart glass increases installation costs and requires use of electricity and a control system for dimming and changing transparency.

Smart window is just one example of smart materials for smart spaces; other smart materials such as smart lighting to increase energy efficiency in smart spaces are still in research and initial production.

Smart Grid: A Smart Grid is a digitally enabled electrical grid that gathers, distributes, and acts on information about the behavior of all participants (suppliers and consumers) in order to improve the efficiency, importance, reliability, economics, and sustainability of electricity services. Research in Smart Grid includes integrating sensor-based systems to improve grid operation and energy distribution (electricity, gas, and water), monitoring and controlling of alternative energy sources aiming at an increase of production efficacy. One example is Irvine Smart Grid Demonstration project [15], collaboration between University of California, Irvine (UCI) and Southern California Edison (SCE). Still in its initial phase, the project's purpose is to demonstrate that Smart Grid is capable of doing efficiently:

- Reduce energy costs to customers by shifting usage loads to off-peak hours or using energy storage to buffer energy at low price.
- Optimize performance of the electric grid, renewable generation and energy storage.

At the same time to understand the process of:

- How Smart Grid technologies connect, communicate, and operate in concert?
- What is the demand of workforce for this new branch/future of energy industry, what are the required skills and job training needed?
- Scalability and ease of reproduction of such demonstration in other parts of the country.

By applying various cutting-edge technologies including energy efficiency home upgrades, advanced home energy management systems, smart meters, smart appliances, solar panels, energy storage systems, electric vehicles, and smart electric distribution circuits, a project concept was successfully deployed around University Hills housing community on the UC Irvine campus. By 2020, it aims to build a complete prototype Smart Grid system, providing safe, economic, efficient, and reliable electric service and integrating with existing power system operations.

Renewable energy: An alternative to energy sustainability in smart spaces is energy harvesting. There must be innovative tools to model and visualize energy expenditure and production and utilize alternative sources of energy (from, e.g., solar panels, wind turbines). Different from other approaches, energy harvesting does not attempt to reduce the energy consumption of the system since it does not withdraw energy from the electrical grid. It instead relies on the environment itself to sustain and do not require alteration to the energy infrastructure of smart spaces. However, it can be integrated into Smart Grid and become a cooperative part in these emerging systems.

Many above approaches address sustainability of various components in smart spaces but only benefit indirectly WSNs in smart spaces. For example, smart glass could be integrated with energy harvesting technologies to provide power for WSNs. Smart Grid could help to reduce energy concern of WSNs but explicit wiring from Smart Grid infrastructure to WSNs would defeat their non-intrusiveness goal. Among sustainability approaches for smart spaces presented above, renewable energy sources and energy harvesting techniques have a significant direct impact on energy sustainability of WSNs. Micro-scale energy harvesting systems augment traditional sensor systems with energy harvesting capability to reduce energy concern and prolong their lifetime. However, micro-scale energy harvesting systems have its own challenges that will be summarized in the next section. Energy harvesting revolutionizes traditional sensor systems but their inherent challenges demand novel solutions at all levels of system stack, from hardware to software layers in order to achieve its promising sustainability and efficiency.

2.2 Energy Harvesting as a Promising but Challenging Solution for WSN in Smart Spaces

The benefits that energy harvesting technologies bring to WSNs include but not limited to:

Energy sustainability: Systems operate autonomously on their own renewable energy sources which can be harvested and potentially sustain the system for unlimited time only subject to hardware lifetime.

Environmental friendliness: Energy harvesting mechanism utilizes green energy sources from the surrounding environments instead of non-rechargeable batteries which must be discarded after use and might not be recyclable. In inaccessible locations, human cannot replace batteries and are forced to discard old sensors while deploying new set of sensors, resulting in high number of unrecyclable sensor motes waste.

Energy scalability: As the energy harvesting WSN in a smart space grows in size, energy resource is scalable if each sensor mote has access to renewable energy sources in the ambience. Each sensor mote's renewable energy source is independent from the others although they could share the same environment. Because of this independency, the system is energy scalability.

Low maintenance cost: Users have less concern on the deployment and maintenance of these sensor networks. No wire or alteration to the current energy infrastructure of smart space is needed. Cost in maintenance is much lower compared to battery-powered systems.

Pervasiveness: Micro-scale energy harvesting systems can be easily deployed in smart spaces as plug-and-play devices. They can spread and integrate into everyday life's activities effortlessly and non-intrusively.

On one hand, energy harvesting technologies bring many benefits to WSNs including energy sustainability. On the other hand, micro-scale energy harvesting systems for WSNs face several challenges and require good management framework in order to attain the aforementioned benefits. Some of the challenges are due to the inherent nature of renewable energy sources; some are general challenges in WSNs that are exaggerated by the dynamic energy sources. We provide a brief overview of these challenges below:

Spatial and temporal variations: Variation in scavenging energy from environment leading to uncertainty in energy availability during system operation challenges the sustainability in WSNs. For example, harvesting energy through solar cells highly depends on the time of the day and exposure to direct sunlight at a specific location. Figure 4 shows our measurement in a building on campus at UC, Irvine. Figure 4a shows the solar harvested energy profiles at the same location for several days in a week. Figure 4b shows the harvested energy profiles at several locations around a building on campus on a same day. Both show large variation in their energy profiles.

The variations in energy harvesting profiles depend on a number of factors. For natural energy sources, many of them depend on time of the day, ambient temperature, season and surrounding objects. Artificial sources on

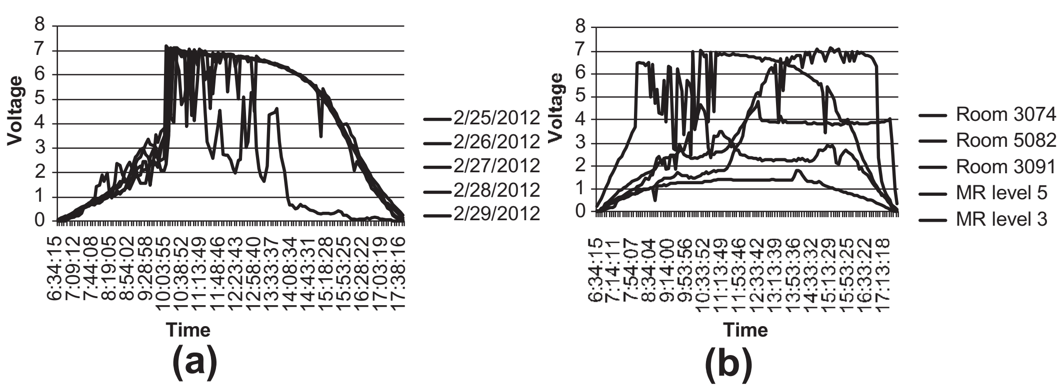

Fig. 4. 4(a) temporal variation and 4(b) spatial variation in solar energy profile.

the other hand depend largely on schedule and intensity of human and system activities. For example, the amount of energy harvested from artificial lights in a smart building depends on schedule of the light system, frequency, and duration of people occupancy (smart lights have occupancy sensors).

Heterogeneity: Heterogeneity arises not only due to the multitude of sensors that have different resource needs (e.g., camera vs. motion sensor) and different configuration options, but also due to possibility of multiple harvesting from multiple renewable sources. While heterogeneity in energy harvesting subsystem(s) enhances sustainability for a micro-scale energy harvesting system, it increases the complexity of the power/energy management framework of a system.

In addition to the challenges of variation and heterogeneity in energy harvesting systems, to design an efficient micro-scale energy harvesting system, we must consider other system requirements such as:

Varying demand of applications: In smart spaces, unsupervised events and environmental changes trigger various applications to run in the systems. Varying demand of applications manifests itself in application quality requirement and urgency of response (and/or criticality). While aiming for the highest application quality and fastest response can resolve the issue, it incurs high energy cost, over design and complexity in implementation. Thus, this is often not feasible in practice. The variation in application demand appears both in time and space domains. While change in frequency of events implies variation in time, higher urgency of response to sensing devices at important locations (e.g., the entrance of a building as opposed to other entry ways) refers to spatial variation. To cope with both variations in application demand, or implicitly energy demand and variations in energy harvesting sources is a very challenging task.

Planning/deployment scalability: Since energy harvesting is enabled in a vastly distributed scheme for WSNs, the scalability in efficiently capturing environment-dependent renewable energy sources through simulations, profiling, and/or measurement is a key challenge.

Size and cost: As for any system, size and cost are important factors in designing a micro-scale energy harvesting system. Size, cost, packing constraint, efficiency of hardware components, software support must all be considered in a holistic approach.

The dynamicity of the challenges above creates new and exciting research problems in harvesting-capable WSN. In particular, it creates a shift in research focus from energy-efficient to energy-neutral approaches, i.e., from optimizing energy consumption and prolonging battery lifetime to optimally adapting systems to deal with unstable energy sources. Designing a sustainable wireless sensor network (with replenishable but fluctuating energy supply) while optimizing system performance or application quality of services is a formidable challenge. To tackle these challenges is a rewarding research task.

There is a large body of research in the literature on energy-efficient techniques for traditional non-rechargeable battery-powered systems. For example, Han et al. [23], Cetintemel et al. [24], and He et al. [25] optimize energy consumption to prolong lifetime of finite charge batteries and as a result, lifetime of the whole sensor network. These approaches are designed for and suited to traditional continuously discharging battery systems. In contrast, renewable energy sources replenish themselves. This fundamental difference coupled with novel challenges created by energy harvesting source characteristics requires novel solutions.

In Section 3, we will review the model of micro-scale energy harvesting systems and state-of-the-art research from both hardware and software points of view. The challenges of designing sustainable micro-scale energy harvesting systems for smart spaces and open research problems will be categorized and presented in Section 4.

3. MICRO-SCALE ENERGY HARVESTING

We first present a system model for single micro-scale energy harvesting systems followed by their challenges and research at all layers of hardware/software and highlight some micro-scale energy harvesting system prototypes. Network model for micro-scale energy harvesting WSNs is also described together with challenges and research arisen at the network layer in distributed energy harvesting systems.

3.1 System Model

There are four main components in a micro-scale energy harvesting system: (a) energy transducer (harvesting devices), (b) energy harvesting circuit, (c) energy storage subsystem, and (d) the load which can be a sensor board or a specific micro device running a software stack and applications. Figure 5 shows the hardware/software layer overview of a micro-scale energy harvesting system. Other hardware components of the load device include sensor(s) and radio chip. The software stack comprises network, OS features, and the application running on such platform.

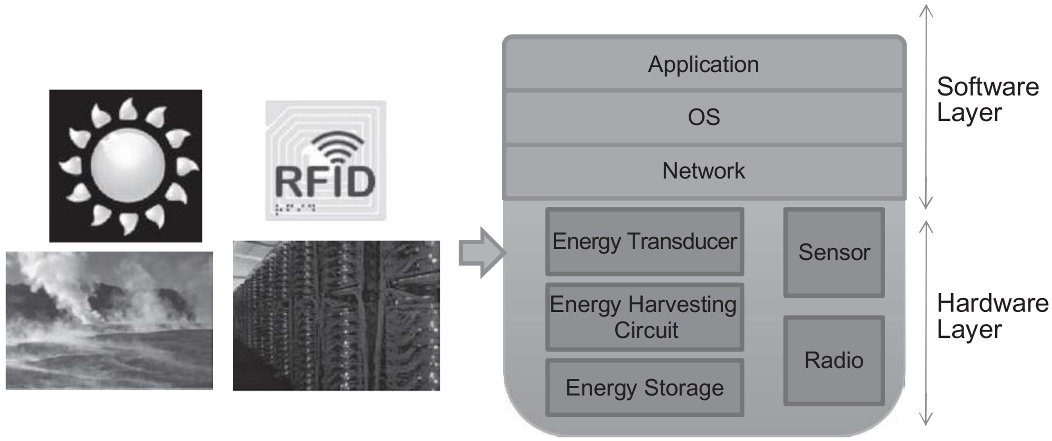

Fig. 5. Micro-scale energy harvesting systems.

Energy harvesting from the surrounding environment are subject to availability of energy sources both in time and in space. Classification and characteristics of energy harvesting sources are presented in Section 3.2. Energy goes through several transformation steps before being used by the load; each step has its own efficiency: conversion efficiency, harvesting efficiency, buffering efficiency, and consumption efficiency [32].

Depending on the location where sensors are deployed, cost, size constraint, and power demand, a feasible energy source(s) is identified and suitable energy transducers are chosen. In order to select and set up the right configuration for harvesting devices, designers must understand harvesting device characteristics and their setup options. We discuss hardware components including energy harvesting circuit and energy storage sub-system, their characteristics, and configuration options in Section 3.3.

A good hardware layer for micro-scale energy harvesting system is capable of efficiently harvesting energy and storing energy in a storage subsystem. However, as the energy storage replenishes at a varying rate, it is necessary to have an energy management scheme to address the challenges of sustainability and variations, to guarantee continuous services and application requirement satisfaction. Software stack for energy management in micro-scale energy harvesting systems will be discussed in Section 3.4. Section 3.5 discusses challenges in networked micro-scale energy harvesting systems. A case study of our energy harvesting management framework, QuARES is presented in Section 3.6.

3.2 Energy Harvesting Sources

Energy harvesting sources are those available in the surrounding environment; which has the potential to provide energy for powering in full or in part sensor networks in smart spaces. Energy harvesting sources can be classified into two groups according to characteristics of its source:

- Natural sources are those available readily from the environment such as sun light, wind, and geothermal heat.
- Artificial sources are those generated from human or system activities. They are not part of the natural environment. Examples are human motion, pressure on floors/shoe inserts when walking or running, and system vibration when operating.

Table I shows different energy sources for energy harvesting, their source type, and typical harvesting power. System designers need to take energy harvesting source type into account for two reasons. First, natural sources are influenced by natural factors such as weather, temperature, season while artificial sources are influenced by schedule and impact of human and machine systems. This will impact, for example, prediction mechanism of each source type. Second, natural sources do not cost extra energy to generate. There could be effects on the environment through harvesting natural sources at large scale which is outside the scope of our study of micro-scale energy harvesting systems. Artificial sources, on the other hand, require human/machine systems to expend energy in order to generate ambient harvestable energy. This generating energy should not be considered as a cost if it is used mainly for other purposes such as lighting a room or running a computer system. The available harvestable energy is thus just a side effect of this process. However, if the generating energy is mainly used to generate harvestable energy it is considered a cost.

Table I Energy harvesting sources.

Energy source	Type	Typical power
Outdoor solar light	Natural	100 mW/cm^2 (outdoor),
Indoor office light	Artificial/natural	100 μW/cm^2 (artificial light)–10 mW/cm^2 (filtered solar light)
Ambient radio frequency	Artificial	0.001 μW/cm^2 (WiFi)–0.1 μW/cm^2 (GSM)
Thermoelectric	Artificial	60 μW/cm^2
Vibration	Artificial	4 μW/cm^3 (human motion) 800 μW/cm^3 (machines)
Ambient airflow	Natural/artificial	1 mW/cm^2
Acoustic noise	Natural/artificial	960 nW/cm^3

This could happen, for example when a light bulb is turned on for some extra hours just to charge a sensor equipped with solar panels; or radio spectrum is generated to charge a RFID sensor.

Energy harvesting sources can be classified into four groups based on two characteristics: controllability and predictability [26]. Controllability means whether an energy harvesting system has full/partial control over its energy harvesting sources or not. Predictability means the degree to which the energy harvesting source can be modeled and predicted. The four groups are:

- *Uncontrollable but predictable:* Natural sources are typically uncontrollable but some sources exhibit or follow predictable patterns. For artificial sources, the schedule and impact of the generating systems or human can be known beforehand or predicted so energy harvesting availability is predictable to certain degree. However, they often operate independently from the harvesting systems and hence they are not controllable.
- *Uncontrollable and unpredictable:* Natural sources can be uncontrollable and behave in a totally random way. For instance, in mobile systems, the surrounding harvesting energy sources are uncontrollable and unpredictable due to the stochastic mobility of the systems.
- *Controllable and predictable:* Artificial sources can be fully controlled if a central control system, which is authorized to and is capable of coordinating both the generating system and the harvesting system, exists. For example, a control system schedules turning on/off the lights or sending energy wirelessly via radio frequency to create harvesting opportunities for harvesting systems. It is also possible to predict the availability of artificial sources to some extent given the schedule and impact of human and system activities.
- *Partially controllable:* Artificial sources can be partially controlled by human or systems but with uncertain result in energy harvesting.

Among these groups, the first group has so far yielded the most research interest, the energy sources cannot be controlled but its behavior can be modeled to predict the energy harvesting availability with some error margin. Other groups also present many interesting and challenging research problems but have been less explored.

Degree of predictability, however, varies according to energy sources and the granularity of prediction. Prediction on a daily basis yield higher accuracy than fine-grained prediction such as minute or second intervals. Nevertheless, prediction at various time intervals is still important; for example, long-time coarse-grained prediction is sufficient for offline planning while short-time fine-grained prediction is more useful for online instant adaptation. All in all, a thorough understanding of the target energy harvesting source is crucial in planning and building an efficient harvesting system.

Next, we briefly look at types of load in micro-scale energy harvesting systems and their corresponding energy consumption demand in order to justify the extent or benefit of using energy harvesting technologies in WSNs.

Table II shows a summary and comparison of such low power sensor boards. There have been several energy harvesting prototypes being built with Micaz, Telos [27,10], or Eco node [38].

General sensor boards provide computation and communication capacity and allow various sensor plug-in via analog, digital inputs, and interfaces. Table III summarizes our study of different types of sensors in the market and its corresponding typical power consumption. They can be classified into three classes as follows:

- *Low power sensors:* Temperature, acceleration, humidity, heart rate/ECG sensors require power in the range of tens of mW.
- *Medium power sensors:* Low-power image capture, acoustic, magnetic require hundreds of mW power.
- *High power sensors:* Motion detection, low-power GPS needs several-W power supplies.

This study shows that micro-scale energy harvesting systems are good potential platform for general sensor boards and low power sensors since their power range matches. Micro-scale energy harvesting systems could also support medium and may be high power sensors but it would require more sophisticated control. Many applications do not need to run at full duty cycle, individual components such as sensors, processor, or radio can be put into sleep mode when needed. The total power consumption hence is adjusted according to duty cycle rate. These decisions are often handled by software stack or middleware layer with understanding of both application requirements, its tolerance of low duty cycle and status of energy harvesting.

In the next sections, we describe the hardware components and software stack in micro-scale energy harvesting systems.

3.3 Hardware Components

In this section we discuss essential hardware components that build up an efficient energy harvesting system. We present different options for each component and trade-offs between cost, size, efficiency, lifetime, and other important factors.

Table II Sensor Boards.

Sensor Board	Developed by	Voltage	Current (mA)			Max power (mW)	Special features
			Processor (Active)	Radio Rx	Radio Tx		
Mica	UC, Berkeley	2.7–3.6V	6.4	3.8	12	55.2	TinyOS
Mica2	UC, Berkeley	2.7–3.3V	8	10	27	95	TinyOS
TelosB	UC, Berkeley	2.1–3.6V	1.8–2.4	23	21	75	Low power, fast wakeup
Medussa	UCLA	1.5V	5.5	3.8	12	26.55	Multiple Processor
Amps	Rockwell	3–3.6V	76	27	50	378	DVFS
Wins/Sgate	Rockwell	3–3.6V	127	122	221	1080	DVFS, Linux
Pico	UC, Berkeley	1V	1	N.A	N.A	10	
Eyeys	European Research Grp	1.8–3.6	400 μA	12	3.8	12.6	Low-end sensors, OS

Types of loads: Since the typical power harvested in micro-scale energy harvesting systems is in the range of mW or less (see Table I), loads of micro-scale energy harvesting systems should have power consumption in the same range. Fortunately, there are various types of sensor boards developed with low power consumption in the range of mW or with duty cycling which reduce the power consumption to the same range of mW.

Table III Sensor types and typical power consumption.

Sensor type	Power consumption
Temperature	9.35 mW
Acceleration	10 mW
Humidity	3–15 mW
Heart rate/ECG	19.8 mW
Low-power Image	80 mW
Acoustic	540 mW
Magnetic	1.5 W
Motion detection	4 W
Low-power GPS	5 W

3.3.1 Energy Transducer

Energy transducers are hardware devices transforming energy harvesting sources into electrical power. Harvesting devices have different cost and power conversion efficiency due to different materials. For example, mono-crystalline silicon, polycrystalline silicon, or thin films are alternative materials to build solar panels. Typical solar cell efficiency is around 18% [27].

Design consideration papers [36,46,14] focus on designing efficiently a micro-scale energy harvesting system and making important design decisions. Taneja et al. [36] gives some guidelines for selecting hardware components in a micro-scale energy harvesting system and their corresponding size. Based on empirical estimation of load's power requirement, daily energy requirement for the system is computed. This requirement and estimation of energy harvesting drive the solar panel sizing and storage selection process. For example, in the case of Hydro-Watch system deployed in a forest where each node has only about half an hour sun light each day and given efficiency of each hardware component, they suggest that solar panel should be sized so as to produce power output of 15 times power requirement during its limited exposure time to direct sun light. This over design ensures that the system has enough energy in storage to sustain operation during non-harvesting period.

3.3.2 Energy Harvesting Circuit

Energy harvesting circuit is one of the most crucial parts of the hardware in an energy harvesting system. It calibrates and maximizes the output from the energy transducers, routes the energy to power the load directly or deposits into the energy storage subsystem, and manages charging algorithms. It possibly monitors the transducer output and energy storage status, and makes this information available to upper software layers. Each of these tasks is often handled by individual hardware elements. In this chapter, we call them in general the energy harvesting circuit.

There is usually a gap between the supply and the load voltage, thus, voltage regulators are necessary to bridge this gap. The options are either linear regulators or switching regulators and the trade-off is between their conversion efficiency and generation of clean, stable output power. Switching regulators could be diode, buck, boost, or a combination of buck-boost regulators such as pulse frequency modulation (PFM) regulators. Buck performs voltage step-down while boost performs voltage step-up. Among these options, PFM regulator is considered most effective since it has both a switching capacitor regulator to avoid wasting energy in diode at low voltage and a buck converter to prevent shorting the input and output. Other components might be needed such as DC/AC or AC/DC adapters depending on the type of current generated by the energy harvesting process and the type of current accepted by the load [92].

Furthermore, most energy harvesting source has a special voltage–current (*I*–*V*) characteristics curve. In Fig. 6, we show the model of *I*–*V* curve for a solar panel. For micro energy harvesting systems, empirical characterization and manual calibration of energy transducer is often required to obtain this *I*–*V* curve model. Measuring, modeling, and understanding *I*–*V* curve is important since it reveals the Maximal Power Point at which the highest power is attained by the harvesting circuit. However, the *I*–*V* curve for a harvesting device is dynamic as it is sensitive to ambient factors such as temperature or solar irradiance level. Figure 6 shows the *I*–*V* curves under various temperature and irradiance condition (extracted from a model of Sunpower A300 solar cell). It shows that corresponding Maximal Power Points changes under different environmental conditions. For AC sources such as vibration, Maximal Power Point is related to the resonant frequency of vibrating devices and magnitude of the physical oscillation. Operating energy transducers at Maximal Power Point gains significantly more power than sub-optimal points. Therefore harvesting circuits should employ Maximal Power Point Tracking methods to improve their efficiency.

Maximum Power Point Tracking (MPPT) is a practice to maximize power output by adjusting the impedance load of the harvesting transducers to match the varying load of transducer devices. Many methods have been proposed for macro-scale harvesting systems, a survey is given in [31]. Chou and Kim [40] classifies MPPT approaches for micro-scale energy harvesting

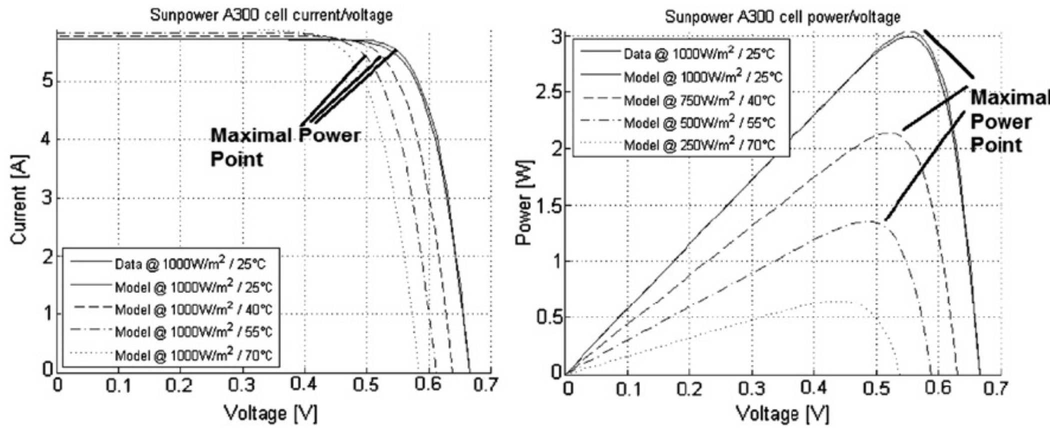

Fig. 6. I–V characteristics of an example solar cell.

systems (with limited memory and stringent energy consumption requirement) into two categories: load matching and supply side MPPT. In load matching approaches [45], the load is adjusted by duty cycling, dynamic power management (e.g., DVFS), or other power management techniques to match with energy transducer load and hence maximizing the utility of power. This MPPT approach is very application-specific and can only be managed at run-time by software stack.

The second approach, supply side MPPT, is further divided into two types: sensor-driven MPPT and perturbation-based MPPT. In the sensor-driven MPPT, sensors are employed to measure environment conditions, their values are used to determine the optimal load corresponding to Maximal Power Point from a look-up table. This method is simple to implement and fast but it blocks a portion of the limited memory to store the look-up table. In addition, sensors consume energy themselves and are subject to aging and other forms of deterioration which might require re-calibration.

Perturbation-based MPPT methods include open circuit voltage, short circuit current, hill climbing, and I–V curve sweeping. One such method is called Fractional Open-Circuit Voltage in which $V_{\mathrm{mpp}} \cong K^* V_{\mathrm{oc}}$ where V_{mpp} is voltage at Maximal Power Point and V_{oc} is open circuit voltage. K is a constant, typical between 0.71 and 0.78 for photovoltaic module [29,30]. This approximation method has low overhead and does not require many sensors or calibration at the trade-off of lower accuracy.

In curve sweeping method, the I–V curve is profiled at run-time using sensors and re-calibrated if needed. For windmill, rotation speed sensor can be used. Direct measurement of ambient factors and voltage/current values provides better tracking of Maximal Power Point but accurate measurement requires disconnecting the load from harvesting sources temporarily; this can work with a secondary power source such as battery or supercapacitor in micro-scale harvesting systems. This method is more robust at the trade-off of complex MPPT circuit and higher overhead both in time and energy consumption.

The efficiency loss can range from 30% to 90% of the available power without MPPT [32]. The level of accuracy of MPPT methods increases at the expense of energy cost. A system designer therefore must consider all methods carefully, taking into account not only accuracy and energy consumption but also timing and memory requirements.

MPPT methods can be implemented in hardware (analog circuit) or software (running on the Main Control Unit, MCU). The challenge is to design a MPPT method with small time and energy overhead while achieving high accuracy. According to [40], shared MCU for control and power management potentially can exploit application knowledge to further improve system efficiency while dedicated MPPT control enables modular and reuse of energy harvesting subsystems. Implementation in MCU consumes more power but it could make low power if duty cycling is used properly and without affecting other tasks running on the same MCU. Software implementation is reusable in any system but it is unable to re-calibrate energy transducers. On the other hand, implementation in analog circuit consumes very low power and allows continuous and quick response to Maximal Power Point changes. The hardware for such MPPT, however, must be designed for each specific system.

From another point of view, Taneja et al. [36] argue that energy transducer such as solar panel can be chosen to operate near its Maximal Power Point given the combination of the load and energy storage. Hence they do not use MPPT in their design of Hydro-Watch harvesting circuit but select solar panel that best matches the system load and energy storage sub-system.

Other setup configuration options are also important:

- *Multi-dimensional array of harvesting transducers:* Multiple harvesting devices can be combined in series or in parallel to form an energy sub-system and increase either the voltage or current and the generated power. The array is reconfigurable at run-time to adjust output voltage or current dynamically. However, such an array of harvesting transducers is subject to size and packaging constraints of the whole system.

- *Heterogeneous/homogeneous harvesting systems:* If one source of energy harvesting is not sufficient to provide energy for system operation, several energy sources could be harvested at the same time to complement each other and increase overall energy. This adds complexity in the harvesting circuit because each energy source requires a different energy transducer. In addition, several MPPT methods and/or measurement circuits must be running at the same time for energy harvesting sources with different I–V characteristics. Furthermore, each harvesting source might require independent energy storage with specific charging algorithm for efficiency purpose. Because of this separation and independence of resources, heterogeneous harvesting systems often have an energy harvesting subsystem for each energy harvesting source [14,33]. Heterogeneous sources also add complexity to the management circuit which handles energy routing from different sources to power the load or charge a backup battery.

3.3.3 Energy Storage Subsystem

System might be powered directly from the energy harvesting sources but large variations in the energy sources will make the system unstable. Therefore to smooth out the effect, energy storage/buffer is often used to provide continuous operation for the system. There are currently two choices for energy storage in an energy harvesting system: rechargeable batteries and supercapacitors (also called ultracapacitors or electrochemical double layer capacitors). Different batteries and supercapacitors have different operating voltages; they require different charge algorithms and complexities. We give a brief comparison of batteries and supercapacitors:

Batteries have higher energy density (more capacity for a given volume/weight). Rechargeable batteries can be re-charged multiple (limited) times and are subject to aging and rate capacity constraints. Characteristics of four types of rechargeable batteries are presented in Table IV. Sealed Lead Acid (SLA) and Ni-cadmium are used less often because of their low energy and power density. According to [46], there are several trade-offs between Nickel-Metal Hybrid batteries (NiMH) and lithium-ion batteries (Li-ion). Li-ion batteries are more efficient, have longer lifetime but are more expensive and require a more complicated charging circuit. Especially, they might not accept charging at low rate which often happens in energy harvesting circuits. Furthermore, batteries characteristics could vary at different operating temperatures. This is especially true for energy harvesting systems which are exposed to harsh conditions like strong wind, direct sunlight, and thermal heat.

Table IV Comparison of rechargeable battery types (adopted from [35]).

Battery type	Energy density (MJ/kg)	Power density (W/kg)	Efficiency (%)	Discharge rate (% per month)	Recharge cycles
Sealed lead acid	0.11–0.14	180	70–92	3–4	500–800
Ni-cadmium	0.14–0.22	150	70–90	20	1500
NiMH	0.11–0.29	250–1000	66	20	1000
Li-ion	0.58	1800	99.9	5–10	1200

Supercapacitors do not have aging problem, they offer higher lifetime in terms of charge-discharge cycles. They have high power density but low energy density (for the same amount of energy to store, supercapacitors need much larger volume than a rechargeable battery). High leakage (almost linear) even when idle is an disadvantage. Another problem with supercapacitors is the cold start, which was addressed in [34] using feed-forward PFM (pulse frequency modulation).

Chou and Kim [40] suggests hybrid schemes for energy harvesting storage to compensate each other and utilize advantages of both energy storage technologies. Regardless of type of storage, they can be combined in an array to modify operating voltage, current, and adjust impedance load to maximize efficiency for the whole circuit.

3.3.4 Case Study of Micro-Scale Energy Harvesting Systems

Recent research has enabled wireless sensor motes to have capability of harvesting energy from surrounding environment, i.e., micro-scale energy harvesting systems. Many prototype platforms have been built successfully including Heliomote [10], Prometheus [27], Everlast [38], Ambimax [14,77]. Beside solar and wind, technologies have made it feasible to harvest from other renewable sources such as vibration, RFID, geothermal, human motion [11–13]. We present here several working prototypes of micro-scale energy harvesting systems, many of them have been deployed in real- life applications.

Prometheus[27] is one of the first design for micro-scale solar energy harvesting systems, it focuses mainly on the energy storage subsystem and there is no MPP tracking. It argues that in most latitudes we only expect a few hours of direct sunlight, therefore the systems need large buffers to store and power node through the night. In their design, there are a primary buffer and a secondary buffer. Supercapacitor is chosen as primary buffer for its longer lifetime and capability of frequent pulse charging.

However, larger supercapacitors have greater leakage current. Prometheus chooses Lithium battery as secondary buffer. Secondary buffer is a backup which is not charged/discharged frequently but holds backup energy for an extended time. A rechargeable battery is more suitable than a supercapacitor for secondary buffer because of its low leakage and higher energy density and voltage for a single cell.

In addition, given charging, discharging, and leakage rate, Prometheus finds the theoretical optimal capacitance of supercapacitor. It also proposes selecting and configuring components carefully, e.g., connecting two supercapacitors in series, in order to reduce leakage and match solar output voltage instead of using MPPT methods.

In their experiments, they run a simple driver program controlling power switch (either drawing from primary energy buffer or secondary buffer to power the load) and sending energy harvesting statistic information to a base station at 1% duty cycle rate. It fully charges the supercapacitor in 2h.

Heliomote was designed at UCLA [10,46]. In the first version, Raghunathan et al. [46] argue that the Maximal Power Point changes slightly within the time of a day, therefore they also avoid using MPPT circuit by carefully selecting choice of battery. They use NiMH as energy storage because the circuit is simplified compared to Li+. In Helimote3, its harvesting circuit is coupled with MPPT method to actively learn solar panel's I–V characteristics and to reconfigure itself to reach Maximal Power Point. Notably, the platform is equipped with on-board measurement providing current output of solar transducer and battery terminal voltage which could be used in tuning or optimizing overall system performance.

The overall efficiency of their energy harvesting and storage subsystem is 80–84%. It is tested running an application of ecosystem sensing at James Reserve Mountain [90]. The measurement results show the system can run at 20% duty cycling which is a very promising result compared to typical battery-powered environment monitoring systems running at 1–5% duty cycling.

Hybrid energy harvesting systems: Due to the intermittent nature of energy harvesting sources, several recent efforts explore possibilities of building hybrid energy harvesting systems with the goal to increase energy harvesting availability overall. Ideally, different sources complement each other for a stable power source in time and in space. Tan and Panda [41] designed a hybrid energy harvesting system consisting of both indoor ambient light and thermal energy harvesting circuits.

Ambimax was designed at UC Irvine by Park and Chou [14]. Ambimax is a hybrid energy harvesting system with both solar panel and wind generator. Each energy source is managed separately by individual energy harvesting subsystem with source-specific MPPT methods to extract maximum power output and to efficiently charge different supercapacitors. A PWM (pulse width modulation) is put between the energy harvesting transducer output and the supercapacitor. This isolation keeps the supercapacitor from degrading efficiency of energy harvesting transducer and also allows harvesting when $V_{\text{source}} < V_{\text{cap}}$, hence improving harvesting efficiency significantly. This PWM switching regulator combined with a comparator and sensing devices create the MPPT circuit. In comparison with Prometheus, Ambimax shows a charging time 12.5 times faster. An improvement of Ambimax was presented in Duracap [34] which includes three supercapacitors to improve system reliability during the cold booting phase.

Carli et al. [33] proposes a similar architecture with independent energy harvesting subsystems but emphasizes on fully analog implementation of MPPT, charging algorithm, and power management.

Indoor energy harvesting systems: Indoor environment has many potential sources for harvesting, each with intensity and availability different from corresponding sources outdoor. The most accessible are light in offices and hallways to be harvested by solar panels. Hande et al. [39] devise a system to harvest energy from fluorescent light in hospital hallways to support routing of patient data in clinics using Micaz motes. Tan and Panda [41] carries out an extensive indoor energy harvesting measurement over 16 months in different settings. EnHantTag [43,42] are small ultra-low- power devices harvesting both light and RFID and supporting novel applications such as tracking personal items and locating disaster survivors. Other energy sources such as kinetic, vibration, magnetic can be harvested as well. inDOOR Energy Harvester is a project at New York University [44] that builds an add-on for hinged doors in order to convert kinetic energy from opening and closing a door to electricity for other grid uses.

In addition to hardware prototypes, designers need tool chain to support the design process such as simulators. *Simulators* allow designers to explore the design space, to evaluate performance of a design candidate in a modeling environment under reproducible inputs and conditions, and to choose optimal configuration options for their micro-scale energy harvesting systems. It can also be used to compare with other designs, topologies, and algorithms.

A solar power simulator S# was developed by Li and Chou [45]. The simulator is a programmable power supply used to simulate or emulate electronic behavior of a solar panel. In the simulation mode, S# takes a current profile and a sunlight profile as inputs, looks up the built-in solar power model and generates a simulated power output. These simulated power profile can be used to test correctness and to measure efficiency of harvesting circuit and energy storage subsystem. The simulation model could be improved to take location and configuration of solar panels and weather condition as input and to generate simulated power output.

Another simulator for micro-scale energy harvesting platform is developed by Jeong [52] at UCLA. This time-event and Matlab-based simulator captures behavior of the main components of a micro-solar energy harvesting system: solar radiation, solar panel, energy storage, and energy harvesting circuit including both input regulator and output regulator. The external environment, in this case solar radiation, is modeled using an astronomical model which computes solar radiation based on the angle between sunlight and the normal of a solar panel. This model is further improved by integrating obstruction model from measured obstruction profile and a weather-metric based model using cloud condition and horizontal visibility. Their estimation method for solar radiation achieves average derivation from real measurement of 24.8%. Other components of the micro-solar energy harvesting systems are modeled based on their electronic properties and model characterization.

In this section, we have presented state-of-the-art research in building efficient micro-scale energy harvesting systems from hardware perspective. In the next section, we present software stack that works in concert with hardware components in order to realize the best benefits of energy harvesting and sustainability goal in WSNs in smart spaces.

3.4 Software Stacks

In traditional battery-powered systems, the conventional ultimate goal is to maximize system lifetime given the limited battery capacity. To address this problem, researchers proposed many energy-efficient and power-efficient approaches, from energy-efficient sensor placement [78–80], routing and communication protocols [82,81,83], low power MAC protocols [85], duty cycling techniques [84] to adaptive data rate [23]. These approaches aim to minimize energy consumption to prolong the system lifetime while barely meeting the requirements of applications.

These assumptions and goals must change in a micro-scale energy harvesting system context. Renewable energy sources are regenerating automatically and they virtually power the systems for indefinite time subject to hardware longevity and environment conditions. A widely used new constraint in energy harvesting systems is energy neutrality, proposed by Kansal et al. [26]. *Energy neutrality* means an energy harvesting system can sustain its desired operation level relying on its energy harvesting sources for indefinite time subject to hardware aging and failure.

Reducing power consumption below the level needed for energy neutrality will not increase system lifetime or system utility. On the other hand, just barely meeting energy neutrality constraint might not utilize all harvested energy. The remaining energy must be stored in the energy storage which has limited capacity and even leakage. Once the capacity for storage is reached, overflowing energy will be wasted while they can actually be used to improve system performance. For example, running 5–10% duty cycling on a micro-scale energy harvesting system and maintaining energy neutrality is possibly feasible but not necessary optimal. A smart approach would be adjusting power consumption according to energy harvesting profile, spending the right amount of energy to optimize system performance and storing the right amount to sustain system operation at time of low or no harvesting activity. In the case of duty cycling for example, extra energy can be used to increase duty cycle rate while still meeting energy neutrality constraint. Energy neutrality is a system constraint while maximizing system performance/utility is a goal. In order to achieve optimal performance, it is important to share information about energy storage status and energy harvesting condition among layers and across network.

One of such important information about energy harvesting to share in micro-scale energy harvesting systems is prediction of future energy harvesting availability. Before going into details of power management using software, we present related research on energy harvesting prediction which is used extensively in power management schemes.

Predicting energy harvesting: Renewable energy sources such as solar energy show predictable patterns (diurnal and seasonal patterns) that can be utilized to predict future energy harvesting availability. Prediction of energy harvesting is very important for simulation, estimating system performance, and planning system activities. However prediction algorithms must be lightweight, have small memory footprint, resource efficient, and low computation complexity in order to run on limited resource sensor nodes.

There are several prediction algorithms to estimate future availability of energy harvesting at coarse-grain (slot-based) level, i.e., every 30 min or per hour. Hsu et al. [47] proposes a prediction model based on

Exponentially Weighted Moving Average (EWMA). EWMA is a method that computes weighted average of data with the weight factors decreasing exponentially. When it is applied for time-series data analysis, by adjusting weight factors, short-term fluctuations can be smoothed out and long-term trend is emphasized. A harvesting period, typically a day, is divided into N_W slots. In this algorithm, N_W is chosen to be 48 for low memory overhead, each slot is 30 min. They assume that on a typical day, amount of energy harvested in a slot is similar to that of the previous day in the same time slot. The energy generated in a particular slot hence is maintained as weighted average of the energy received in the same time slot during all previous recorded days:

$$\overline{x_k} = \alpha \overline{x_{k-1}} + (1 - \alpha) x_k,$$

where $\overline{x_k}$ is the observed value in the slot, $\overline{x_{k-1}}$ is the previously stored historical average and α is a weighting factor. By experiment, Hsu et al. [47] determines a good value of $\alpha \approx 0.15$ where their prediction error is minimum. Their experiments show the absolute error between the predicted and the actual measured energy profile is from 2 to 10 mA out of maximum energy harvesting about 60 mA, which is about up to 16.6%.

Recas et al. [48] notice that EWMA algorithm proposed in [47] is only accurate if the weather is consistent or "typical." Hence, they introduce another prediction algorithm called Weather-Condition Moving Average (WCMA) that does not only take into account the weighted average at certain time slot in a day but also the changing condition in energy harvesting profile throughout a day. A similar principle was exploited in another energy harvesting scheme proposed by Noh et al. [54]. In [48], the predicted energy value on day i, sample $n+1$ is:

$$E(d, n+1) = \alpha E(d, n) + GAP_k (1 - \alpha) M_D(d, n+1),$$

where $E(d, n)$ is previous sample in the same day and $M_D(d, n+1)$ is the mean of D past days at the same time sample $n+1$. GAP_K is a weighting factor measuring the weather condition in the present day relatively to the previous days. WCMA [93] claims lower average error of 9.8% as compared to 28.6% error of EWMA [47] in an experiment consisting of 45 energy harvesting days. Bergonzini et al. [49] compares several energy harvesting prediction algorithms including EWMA, WCMA, one prediction algorithm developed at ETHZ and a neural network prediction method. Results confirm WCMA has better performance in term of average error (less than 10%) over other prediction algorithms.

Jeong [52] and Sharma et al. [50] leverage weather forecast and extract cloud coverage information to improve its solar prediction model. The latter work exploits wind speed to predict energy harvesting from the wind. For solar energy prediction, it uses formulation:

$$\text{Power}(t) = \text{MaxPower}{*}(1 - \text{cloud coverage percentage}(t)),$$

where MaxPower is maximum solar power derived from typical solar radiation at a given latitude, altitude, and a specific time of the year. For wind speed, the prediction formulation is

$$\text{Power}(t) = 0.\,01787485{*}\text{WindSpeed}(t)^3 - 3.\,4013.$$

Renner and Turau [51] propose a method to actively learn energy harvesting profile and adapt the number of slots and duration of each slot at run-time while maintaining accuracy and small memory footprint for energy harvesting algorithms.

There also exist commercial tools for predicting energy harvesting. For example, iPV and iSV are applications available for iPhone. Solmetric iPV [53] is an iPhone app for preliminary site assessment of potential solar energy harvesting. The app is able to record obstruction while users trace the phone along the skyline where the solar panel is deployed. It utilizes available sensors on iPhone such as compass and inclinometer to identify position and elevation of the obstructions and overlay them on the sun plot. Using astronomical model in their database for a given location, the shading effect derived from the overlaid sun plot, a built-in weather station database, and photovoltaic panel model, iPV produces an estimate of monthly solar energy at that location. iSV is a simpler version of iPV. These apps are low cost and easy to use but currently available only to iPhone users. Their documentation and verification of method is limited. Others available tools are SunEye, Solar Pathfinder, and various apps developed for users to estimate solar profile and availability outdoor.

Cross-layer approaches have been proposed to exploit available prediction information to adapt systems accordingly. We classify research work in cross-layer power management schemes into three groups: node layer, operating system layer, and application layer adaptation. Such power management scheme often—consists of three steps: leaning and predicting the harvested energy profile at run-time, adapting power consumption at each layer to match harvested energy, and fine tuning power scaling algorithm to account for battery non-idealities and prediction error.

Node layer: Node layer management refers to management of hardware components such as sensors, radio chips, processors, and possibly energy storage subsystem using software. Kansal et al. [26,56] and Hsu et al. [47] present several power management schemes at node layer. Duty cycling between active and low power modes for the purpose of performance/power scaling is a good option since most sensor networks provide at least one low power mode in which the power consumption is negligible. Hsu et al. [47] adapt duty cycling rate of system to the changes in renewable sources.

OS layer: Operating system controls how tasks such as sensing, processing, and communicating are scheduled using a scheduling algorithm(s). There are works in task scheduling, multi-version scheduling, and dynamic voltage frequency scaling (DVFS) at the OS layer of micro-scale energy harvesting systems. Moser et al. [65,66] propose a task scheduling techniques for energy harvesting systems called Lazy Scheduling, which delays task execution to harvest and store more energy until tasks must be executed to meet their respective deadlines. Liu et al. [67,68] extend these task scheduling techniques with DVFS capability. Steck and Rosing [69] and Ravinagarajan et al. [70] adapts task utility of structural health monitoring applications (coupled with DVFS technique) to maximize accuracy of tasks while sustaining the system under energy neutrality constraint.

Application layer: Specific applications run on general sensor boards, including sending, data processing and data collection protocols. At the application layer of micro-scale energy harvesting systems, there are related works in adapting data quality, data update frequency, and quality of services in order to meet energy neutrality constraint. Moser et al. [71–73] present a system model with different abstract levels of quality. Each level is associated with an energy demand and a corresponding reward. These papers propose an optimal solution using ILP and an approximation dynamic programming technique to allocate energy budget and assign quality level to each time slot in a harvesting period in order to meet energy-neutrality constraint and maximize the total reward at the same time. Noh et al. [54] proposes a minimum variance slot-based energy budget allocation for systems which prefer steady level of operation. This energy budget distribution scheme is suitable for systems whose level of operation is stable. For applications with varying constraints and requirements, more dynamic energy budget schemes are required.

Software support for micro-scale energy harvesting system is unstructured and it is difficult to guarantee all approaches work in concert with each other to produce the optimal result. A middleware layer providing software services and information about energy harvesting conditions, statistics, and battery status and allowing tuning parameter (e.g., changing duty cycle rate, selecting scheduling algorithm and/or budget allocation scheme, and turning on/off database services) is desirable. Middleware layer will play an important role to connect hardware and software layers, enable cross-layer adaptation, and system performance optimization given both system and application requirements (timing, energy, quality of services, quality of data, etc.). In Section 3.6, we will show an example of middleware framework [87] which exploits application awareness and prediction information of energy harvesting profile to maximize application quality of data.

In a broader scale, networks of micro-scale energy harvesting systems presented in the next section, middleware and network layers will have a crucial role. They connect systems in the network and enable sharing energy harvesting information beyond a single system's boundary. Sharing energy harvesting context information allows networked systems to coordinate and maximize performance at a larger scale.

3.5 Networked Micro-Energy Harvesting Systems

So far, we focused on individual micro-scale energy harvesting systems. In this section, we present the model and structure of micro-scale energy harvesting networks and related research. Many applications in smart spaces leverage connection and information sharing in network to monitor properties of the environment, to detect unsupervised events, and to relay the processed information to a central base station(s). In a network of micro-scale energy harvesting system, applications would need not only the monitoring data but also energy harvesting information collected.

Figure 7 shows architecture of an energy harvesting sensor network. Each micro-scale energy harvesting node has hardware and software components working in concert as described in previous section. A middleware layer is proposed on each node to enable sharing energy harvesting information, cross-layer optimization and in-network optimization. Data from nodes are sent to the base station(s) through application and network protocols. Base station maintains communication with sensor nodes through the same set of protocols. Collected data is stored in a database at base station and/or sent to the smart space applications. With unlimited resources (power, computation unit), middleware layer on base station can also do computational-intensive tasks such as energy harvesting profile prediction, long-term and short-term planning, hardware and software recalibration.

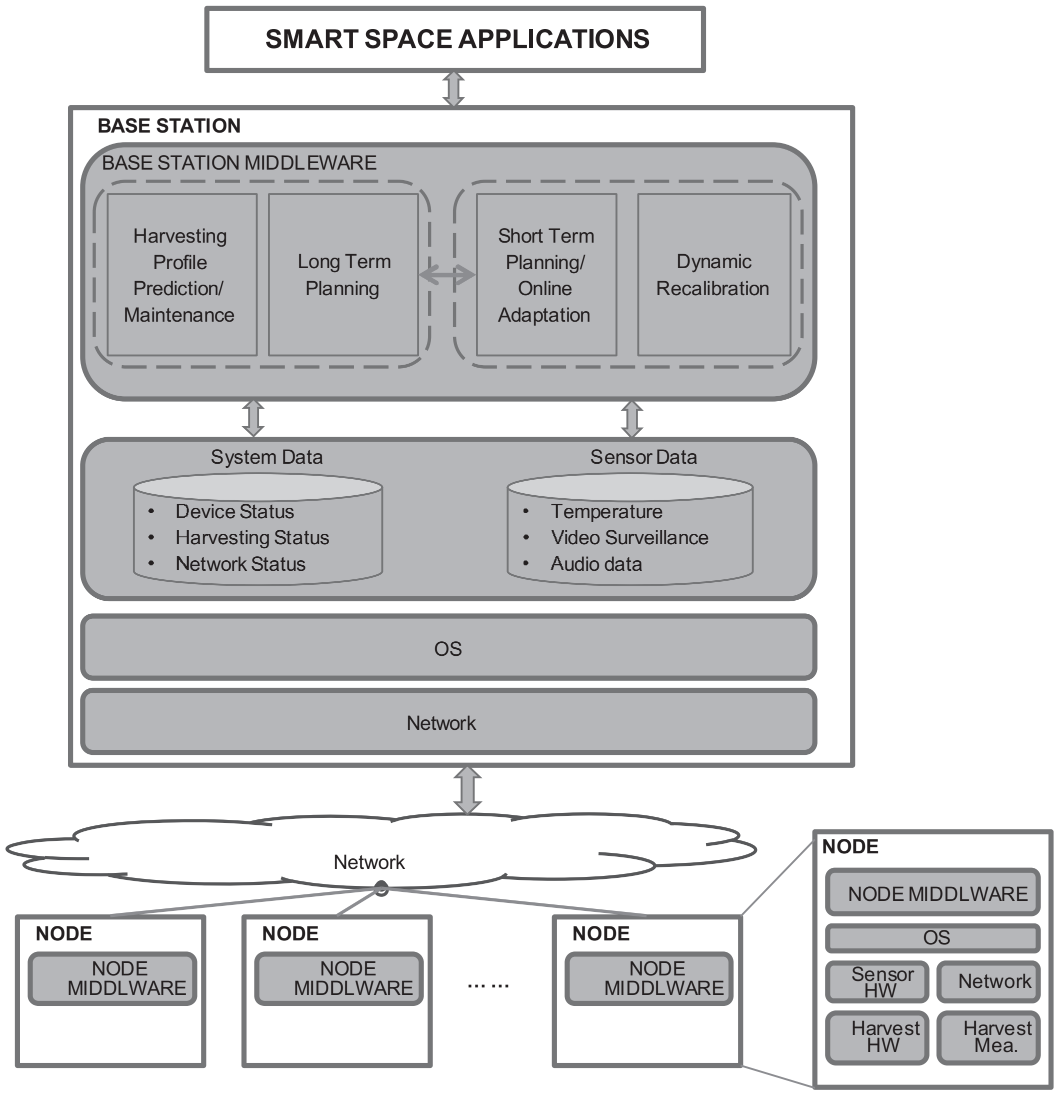

Fig. 7. Energy harvesting sensor networks.

Network layer: The network layer manages communication at packet-level. Packets are sent from source to destination according to network protocols. In micro-scale energy harvesting networks, packets should be routed along paths that do not only ensure delivery but also maintain energy sustainability. Each node sends its own sensor data and also forwards packets for other nodes in the network. Therefore, energy budget for communication on each node must consider both these internal and external data stream. Routing is an important challenge since there are both communication vs. computation trade-off on each node as well as data traffic balancing among nodes according to harvesting capability of each node in the network.

Voigt et al. [57] and Islam et al. [58] modify LEACH, a cluster-based routing protocol for sensor networks to take advantage of energy harvesting. Lattanzi et al. [59], Lin et al. [60,61], Zeng et al. [62], Hasenfratz et al. [63], and Jakobsen et al. [64] modify existing energy-efficient routing protocols to exploit both temporal and spatial variations of renewable energy and to maximize data delivery for sensors. Different from traditional battery residual based routing cost, Kansal et al. [26] propose an enhanced routing cost metric that takes into consideration both the harvesting potential of a node as well as its residual battery level:

$$E_i = w.\, p_i + (1 - w) B_i,$$

where w is a weight parameter, p is the harvesting rate, and B is the residual battery. Communication cost for each link into a node i is

$$c(k_i) = 1/E_i.$$

Bellman Ford algorithms, shortest path algorithms, and variants of these algorithms are deployed to find minimum cost routes between sources and destinations given link cost defined as above.

Application layer: For applications such as storage services in a wireless sensor network, Wang et al. [76] propose an adaptive technique to turn on and off the storage services based on different energy thresholds. Fan et al. [74] and Zhang et al. [75] attempt to maximize data rate and utility-based data rate for data collection applications in energy harvesting WSNs.

Middleware layer: As discussed, micro-scale energy harvesting nodes in the network should communicate to share energy harvesting statistics and availability for power management and in-network optimization. Kansal and Srivastava [55] proposes an energy harvesting framework which actively learns the properties of the renewable energy sources, predicts future energy availability and distributes this information in the network for power management. It suggests several uses of this framework including topology management, clustering, leader election, load balancing, transmission power control, and network routing. In the next section, we present an example of middleware framework for network of micro-scale energy harvesting systems.

3.6 Case Study of QuARES: Quality-Aware Renewable Energy-driven Sensing Framework

QuARES [87] is a middleware framework for energy harvesting systems running data collection applications (Fig. 8). The goal of the framework is to manage harvested energy and utilize it smartly to keep the systems sustainable while maximizing application quality. The framework exploits

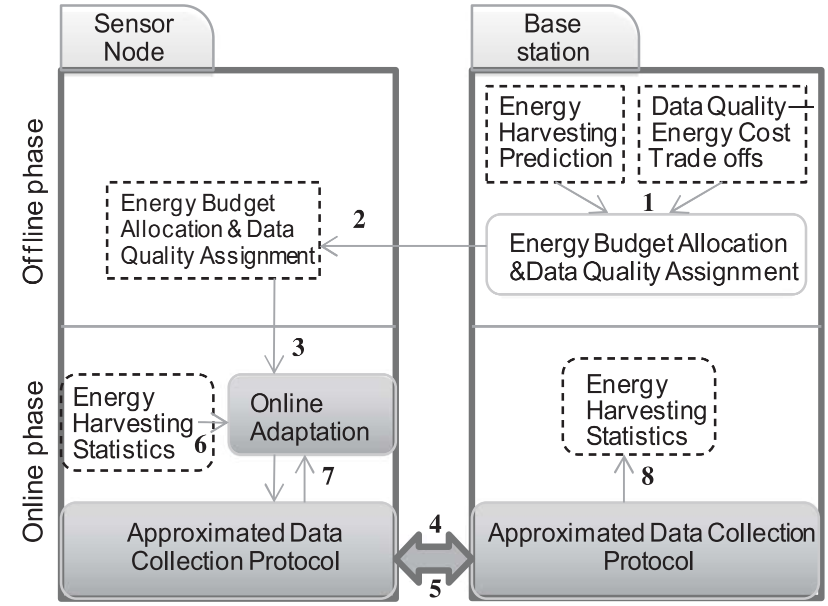

Fig. 8. QuARES framework [87].

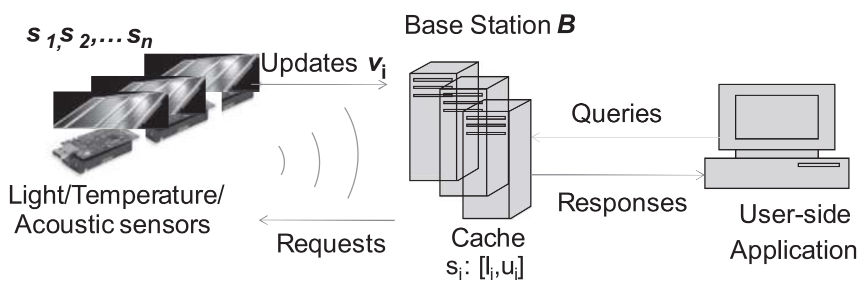

Fig. 9. Data collection application.

application's tolerance to data quality degradation to adjust application data quality and tune system's energy consumption to match energy harvesting capability. While maintaining energy-neutral condition, this framework is the first one among related works to consider and optimize application's data quality in micro-scale energy harvesting systems.

Their wireless sensor system model consists of two main components: a base station(s) and multiple sensor nodes (Fig. 9). Each sensor node has a processor with limited memory, an embedded sensor(s), an analog-to-digital converter, and a radio circuitry. Each sensor node periodically reads its sensor value v_i and sends an update to the base station(s). Sensor value v_i is a property of the environment, e.g., temperature, humidity or sound, that the application needs to collect to monitor the environment. In this work, all sensor nodes are assumed to be equipped with harvesting circuitry.

Harvested energy is accumulated in an energy buffer that supplies power for the sensor node's operation.

Base station B resides at a location with unlimited power and resources. It collects data from sensor nodes and stores them in a cache. The cache contains an approximation range $[l_i, u_i]$, a range-based representation for each sensor node s_i. The base station B is connected to a monitoring application on the user side. The application periodically and sporadically polls sensor nodes through the base station(s) for the monitored environmental phenomenon. The application sends a query Q_j to the base station when it needs data from a sensor node or a set of sensor nodes. Each query Q_j contains data quality constraints A_j.

If the approximation range $[l_i, u_i]$ for sensor S_i in the cache satisfies these constraints, base station B returns an approximated value to the monitoring application. Otherwise, B sends an update request to retrieve latest value v_i from sensor s_i and replies query Q_j with exact value.

In this data collection application model, application quality is the quality of data stored in the cache of the server and in response to the users' queries. This framework focuses in data accuracy and adopts a data quality model from a previous work [23]. Data accuracy requirement is expressed using error margin of actual value v_i, e.g., $v_i \pm 10$ or $v_i \pm 10\%$. Smaller error margin means higher data accuracy and vice versa. However, higher data accuracy in general also requires more computation or communication and thus higher energy consumption. Therefore, error margins can be increased or decreased to meet both data accuracy constraints and system constraints, such as varying energy supply in the case of energy harvesting systems. The energy harvesting management framework exploits this error tolerance to adapt systems to the availability of renewable energy sources.

As explained, data accuracy is modeled in terms of error margin. Error margin δ_i is the bounded difference between the sensing value v_i at sensor node s_i and the approximated response to the query Q_j, i.e., $|r_j - v_i| \leqslant \delta_i$. Both sensor and base station mutually agree on some error margin and maintain the constraints it implies. The approximation range $[l_i, u_i]$ in the base station's cache must satisfy $u_i - l_i = 2\delta_i$ and $l_i \leqslant v_i \leqslant u_i$ These constraints guarantee that whenever base station response to query with its middle-range value $\frac{u_i+l_i}{2}$, this value will not be different from v_i by an amount more than the error margin δ_i. Olston et al. [86] developed a model that relates data quality and energy cost.

The key intuition is to use information of energy harvesting prediction to allocate energy budget for slots in the next harvesting period.

This energy budget allocation must satisfy two constraints: energy-neutral constraints and data quality constraints. They formulate this as an ILP problem with the optimizing goal is to maximize overall data quality. This can be solved using an ILP solver at the base station.

However, prediction of energy harvesting is coarse-grained; it cannot show the exact variations in solar profiles. These variations in solar profiles can cause the battery to overflow or underflow (running out of battery) and either lower the application's data quality or make the system stop operating. There must be an online adaptation process to adjust system such that it will continue to operate with minimal effect on application's data quality. They propose two online adaptation policies: inter-slot adaptation and intra-slot adaptation to cope with variations in solar profile.

These techniques [87] are implemented in a network simulator, QualNet [89]. In comparison with other approaches (e.g., [54]), the system offers improved sustainability (low energy consumption, no node deaths) during operation with data quality improvement ranging from 30% to 70% (Table V).

QuARES is currently being deployed in a campus-wide pervasive space at UCI called Responsphere [88]. They carried out thorough measurement study using measurement kits and solar transducers made by SolarMade [28] for different indoor and outdoor scenarios. In a particular case study, they

Table V Comparison of five different approaches.

	FIX_ERROR ($\delta = 8.0$)	FIX_ERROR ($\delta = 0.5$)	GREEDY_ ADAPT	MIN_VAR	QuARES offline	QuARES offline + online
Average error margin	8.00	0.50	0.348	0.388	0.156	0.159
Total energy consumption (J)	1813	2686	2656	2641	2641	2641
Shut down time for harvesting (min)	0	45	21	7	4	0
Failed responses to queries	0	570	420	196	64	0

measure harvesting potential of different light bulbs for indoor harvesting. Simulation for the case study of hybrid indoor lighting alternatives powering different sensor types shows that QuARES is able to improve system performance overall. QuARES also helps designers to explore the design space and answer important questions such as solar panels size and battery capacity.

To summarize, in this section we have discussed the model of micro-scale energy harvesting systems as well as networks of energy harvesting systems in smart spaces. We explained their components, both from hardware view and software view. We show the opportunities and benefits of energy harvesting technology for micro-scale systems (WSNs) in smart spaces but also different challenges that arise due to the intermittent nature of energy harvesting sources. In the next section, we focus in classifying, and explaining research challenges in micro-scale energy harvesting systems and network of such systems.

4. RESEARCH CHALLENGES

Challenges must be tackled to realize the vision of micro-scale harvesting WSNs in pervasive spaces. We identify challenges in designing a micro-scale energy harvesting system for sustainability in smart spaces in Section 2.2. Research needs to provide holistic approaches to tackle the aforementioned challenges in order to realize sustainability WSNs through micro-scale energy harvesting systems. We classify these research problems into three groups:

During designing phase: in which designers build the hardware layer to realize a micro-scale platform for energy harvesting and consider trade-offs between size, cost, and efficiency to make the right decisions.

During deployment phase: which scopes out the specifications of the smart space, its harvesting capabilities and sensing needs (deployment requirements) to determine a placement of sensor devices for harvesting, sensing, and communicating and any infrastructure redundancy if needed.

During operational phase: that ensures continuous collection of information from smart spaces' WSNs while adapting to changes in environmental conditions, harvesting abilities, and application needs. The operational phase is further partitioned into a periodic sensing plan generation which allocates energy budgets to each device using short- and long-term energy/activity profiles; and an online phase that supports adaptation to fluctuations in energy/activity profiles which could not be captured during offline predictions.

4.1 Designing Phase Research

In this phase, a hardware platform for micro-scale energy harvesting systems targeting specific energy sources is built taking into consideration special *I–V* characteristics of energy sources, low power design constraints, size, cost, and efficiency requirements of the whole systems:

- *Maximal Power Point Tracking* still remains a challenge for various energy harvesting sources. An ideal tracking method would require many sensors to keep track of environmental conditions that affect the *I–V* curve and Maximal Power Point. *I–V* curves need continuous re-calibration as the system and hardware changes or ages. However, a large comprehensive sensor suite would consume significant amount of energy out of precious power (in the range of mW) the system can harvest. Different MPPT methods should be evaluated based on their trade-off between energy efficiency and accuracy in order to choose the optimal method for given energy harvesting sources and systems.
- *Efficient energy storage:* Ideal energy storage for a harvesting system should be able to charge small amount of energy frequently. The charging algorithm should be simple to increase efficiency of energy storage subsystem. The energy storage should have small leakage power in idle state since the system might experience long period of no harvesting and rely on energy storage to sustain until there is opportunity for harvesting again. The discharging algorithm should also be simple and efficient to increase the amount of useful energy for system operation.
- *Heterogeneous circuit:* there is a growth of research in recent years in designing heterogeneous energy harvesting systems with several different harvesting sources. On one hand, this adds more energy to a system and establishes energy resilience when one source is low, the other sources can complement its lack to maintain sustainable energy level of the system. On the other hand, it creates more complexity in management of multi sources simultaneously. It is still a question whether a harvesting circuit should be duplicated for each energy source or if it can be shared among sources.

4.2 Deployment Phase Research

Before the system is deployed, a feasibility assessment must be done and an evaluation of projected system's performance is desirable. Decisions such as where to place sensors, size of energy transducers, size of energy storage to sustain systems, and redundancy degree must be made. To facilitate these tasks, energy harvesting prediction algorithms and tools like simulators are proven to be very helpful:

- *Energy harvesting prediction:* is the problem of studying energy harvesting source behaviors, analyzing historical data available, and extracting patterns in energy harvesting profiles. This information can be used to model energy sources using mathematical or statistical methods and/or other context information such as weather forecast, human, and system schedules. Predicting future energy harvesting has great benefits for other tasks such as simulating, testing, and planning.
- *Smart space assessment:* One important task before deploying an energy harvesting sensor network in smart spaces is to evaluate potentials of harvesting sources in the given space. We need to identify potential harvesting sources and carry out various activities/steps to estimate or measure the availability of such harvesting sources. This estimation will provide understanding of the energy supply and help justify if the system can sustain on these energy harvesting sources and deliver good quality of services for applications.
- *Sensor Placement:* is an interesting problem that is little explored so far in energy harvesting sensor networks. Once smart spaces are accessed and energy harvesting sources are identified and evaluated, sensor locations should be determined subject to constraints such as event, area coverage, and objectives such as minimizing number of sensor nodes, minimizing communication cost, or optimizing data quality.
- *Energy harvestingsSystem and network simulation:* A simulator is useful for repetitive experiments for both individual systems as well as networks of energy harvesting systems. Such simulator can be built on top of existing simulators for sensor/mobile networks such as TOSSIM, NS2, or Qualnet. What is missing in these existing simulator tools is how to modify components such as battery model to take into account energy harvesting activities, harvesting circuits, and energy storage efficiency. In addition, there is a need of energy harvesting traces as input for simulators. These traces should have both temporal and spatial variations and ideally captured from real measurement or generated from accurate models of energy harvesting sources.

4.3 Operational Phase Research

During operational phase of micro-scale energy harvesting system, because of the variations in energy harvesting sources, systems still need to manage energy consumption and adapt themselves according to energy harvesting conditions and battery residual charge, i.e., to maintain energy neutrality. In order to do so, systems must have capability to change or adapt their power consumption:

- *Node layer:* manages hardware components such as sensors, radio chips, sensor boards' processors, and possibly energy storage subsystems using software. As such, a power management scheme at the node layer can adapt techniques such as duty cycling sensors, processors, and radio at highest possible rates to match energy consumption with energy supply from energy transducers.
- *Network layer:* takes charge of sending packets from sources to destinations, selecting paths that ensure delivery and maintain energy sustainability in the network. Maintaining connection and communication is very important in a WSN. As nodes die, part of the network might be isolated and important events/emergency scenarios can be missed or undetected by base stations. The network layer therefore must take active responsibility to control the traffic and set up sustainable routing paths, not only adopting existing techniques from energy-efficient routing protocols but also exploiting inherent characteristics of renewable energy sources in space and in time.
- *OS layer:* where tasks including sensing, processing, and communicating are scheduled by scheduling algorithms. Scheduling algorithms have the control of when and how tasks are executed so that systems can operate smoothly. For example, tasks can be delayed by OS scheduler until sufficient energy is harvested to execute the tasks. Dynamic voltage frequency scaling techniques could be helpful. A task can be executed at higher frequency to meet its deadline if it has been delayed for a significant amount of time or at lower frequency to save energy consumption at the trade-off of delayed finished time. How to deal with both time and energy optimally at the same time is still a challenge. Tasks with multiple versions of execution time and accuracy can be selected for the best system performance while meeting energy neutrality constraint.
- *Application layer:* Many applications have flexibility in the scheduling of their activities and tolerance of certain error margin in the results. Exploiting this flexibility and tolerance, applications can tune their parameters, algorithms to meet energy constraint, and at the same time satisfy application requirements.
- *Middleware for quality*-aware and c*ross-layer power management:* Middleware layer which provides a neat and effective cross-layer management is desirable in micro-scale energy harvesting systems. Middleware layer

is aware of both application and system requirements, hence tuning or adaptation by middleware layer will not only meet the energy neutrality constraint but also maximize quality of services for both systems and applications.

In conclusion, this section presents important research problems, classified into three groups: design phase research, deployment phase research, and operational phase research. These researches are extremely useful in achieving sustainability of WSNs in smart spaces by applying energy harvesting technologies.

5. CONCLUSION

This chapter presents energy harvesting as a promising solution to address energy sustainability for backbone wireless sensor networks in smart spaces. Micro-scale energy harvesting systems make the infrastructure in smart spaces become truly "invisible" and well integrate into everyday's lives. Such systems are autonomous and self-sustainable. They operate perpetually and require little maintenance effort. However to achieve maximum system efficiency, a careful plan from design phase, deployment to operational phase is crucial. In each phase, decisions considering trade-offs of efficiency, performance, and cost must be made. A unified middleware allowing sharing of cross-layer information such as energy harvesting statistics, battery voltage, and providing cross-layer optimization could be a structured way to address challenges in micro-scale energy harvesting systems and to maximize their benefits. In this chapter, we present a model of micro-scale energy harvesting systems and networks from both software and hardware point of view. We summarize state-of-the-art researches and then classify open research problems in micro-scale harvesting systems in the last section.

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